Year: 2017

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DOI: https://doi.org/10.1080/15427560.2017.1332061

Originally published at:
Uhl, Matthias W (2017). Emotions Matter - Sentiment and Momentum in FX. Journal of Behavioral Finance, 18(3):249-257.
DOI: https://doi.org/10.1080/15427560.2017.1332061

Emotions Matter: Sentiment and Momentum in Foreign Exchange

Matthias W. Uhl*

January 2016

Abstract

We introduce news sentiment as a variable that can explain and predict subsequent changes in the USD/EUR exchange rate, and therefore close a gap in the foreign exchange literature. By applying the concept of frequency filtering from the domain of electrical engineering, we show an innovative way of filtering for noise in both news sentiment, but also in price momentum. We find that news sentiment is not correlated to price momentum, and that trading strategies based on news sentiment achieve around twice as high information ratios (up to 0.9) than with trading strategies based on price momentum.

JEL-Codes: G02, G11, G12, G17
Keywords: Behavioral Finance, News Sentiment, Foreign Exchange, Low-pass Filtering, Window Techniques

*University of Zurich, Department of Banking and Finance, Plattenstrasse 14, CH-8032 Zurich, matthias.uhl@gmail.com

1.1 Noise in financial markets

Noise in financial markets is omni-present. This noise can have very different origins, but ultimately, investors can see it in the price of financial assets. Looking through the noise that investors observe every day in the financial markets is therefore paramount in making sense of them and when making investment decisions. The most simple and probably most common way to analyze which direction financial assets are headed is by momentum through the means of moving averages, as they are one of the most common indicators of technical analysis. The idea of looking at moving averages is straight-forward: to look through the noise that financial asset prices exhibit on a daily basis based on a multitude of reasons, such as news or data releases, herding behavior, or fundamentals. The concept of momentum is not new, neither as a characteristic nor as a theory, as Asness et al [2014] nicely show. In fact, Geczy and Samonov [2013] show the existence of momentum is a well-established empirical fact, as the return premium is evident in 212 years of US equity data. The reason why price momentum works is clearly rooted in behavioral aspects, such as herding behavior. If several investors see prices rising, they jump on the trend and buy the financial assets, which in turn increases the price of the assets even further, and so on. More recently, the literature that has examined other behavioral factors that can explain and predict financial asset price movement has centered around sentiment in the news, but mainly exclusively in relation to equity markets. With this study, we want to extend the literature by identifying trends in news sentiment in foreign exchange markets, and namely in the USD/EUR exchange rate, the most highly traded foreign exchange pair, which gets influenced the most by news of different origin, such as macroeconomic, monetary policy, or geopolitical nature. We also extend the literature by marrying the theory of frequency filtering with financial asset pricing theory and show how this can be applied in practice with a trading strategy.

This paper is structured as follows: section 1.2 surveys the literature about the impact of news and the sentiment of the news on financial assets in general and foreign exchange in particular - to the extent that such literature exists, as no literature exists that links news sentiment and the USD/EUR exchange rate. Therefore, we suggest to close a gap in the literature. We then discuss the data in section 1.3 that is used in this paper, and then we construct a model that filters the noise out of news sentiment in order to get a more coherent indication as to whether the trend in news sentiment is positive or negative in section 2.1. We turn to the electrical engineering literature in section 2.2 and employ several harmonic windows with a low-pass filtering approach to do that. In order to cross-check our findings for news sentiment, we filter the USD/EUR exchange rate time series with the same harmonic windows with the low-pass filter for momentum and compare the results for their characteristics. In section 2.3, we construct trading strategies based on both news sentiment and price momentum in order to see whether our empirical findings also hold in the real world. In section 3.1, we conclude. We find that filtered news sentiment can explain subsequent moves in the USD/EUR exchange rate and that it can be used to formulate profitable trading strategies. Compared to price momentum strategies, the information ratio roughly doubles for the trading strategies based on news sentiment. Furthermore, price momentum and news sentiment are not correlated with each other at all, so that we conclude we have identified a new factor for explaining and predicting foreign exchange price movements.

1.2 News releases, sentiment and foreign exchange reactions

In the past decade, the literature on news sentiment and stock market returns has been well established. Earlier studies like Hirshleifer [2001] established first the behavioral dimension in the asset pricing theory, stating that expected returns are determined not only by risk but also by misvaluation due to inherent behavioral biases of investors. More concretely, Mullainathan and Shleifer [2005] identified that there is a market for news, and that readers hold beliefs that they like to see confirmed. This suggests that readers extract - knowingly or unknowingly - sentiment based on their personal cognitive biases. In fact, Tetlock [2007] was one of the first to nicely document that sentiment in the news predict future stock market returns, applying a so-called bag-of-words approach, in which the article is scanned for either positive or negative words. Indeed, Tetlock [2007] only considers negative words and concluded that these are predictive of future negative returns, but he was missing to find a link between positive sentiment and subsequent positive returns. Since Tetlock's [2007] study, the means to extract news sentiment became more complex and sophisticated, drawing from natural language processing algorithms that are able to account for not only positive and negative words, but also account for the context. For example, Leinweber and Sisk [2011] as well as Uhl et al [2015] have made use of a sophisticated dataset called *NewsAnalytics* from Thomson Reuters by identifying news sentiment scores that can explain and predict stock returns. In both studies, a sub-sequent and positive relationship is identified between stock returns and news sentiment. Successful trading strategies are constructed that generate positive alpha, even if the investment time horizon spans over several months. Uhl et al [2015] show that equity returns can be explained and predicted by both company-specific news sentiment (i.e. a bottom-up indicator constructed from invidual company news) as well as a macro-specific news sentiment factor (i.e. a top-down indicator comprised of political, monetary and macroeconomic news).

However, to the best of our knowledge, news sentiment has not been examined in connection with foreign exchange rates, and namely with the USD/EUR. Therefore, we think it is worthwhile doing so. Past literature on foreign exchange rate movement has centered around the impact of news during macroeconomic news releases, but not on the sentiment of these news. Edison [1997] hints at sentiment in the news by examining the response of exchange rates to economic news. He finds that the news is associated with the surprise component of the monthly release of six US macroeconomic variables. The results in Evans [2002] point away from exchange rate models with a common-knowledge (CK) environment dominated by a small number of macro variables. Rather, the findings point towards models with richer informational structures in which the sources of non-common knowledge (NCK) news can be identified. One possible source could be news sentiment. Galati and Ho [2003] find that macroeconomic news have an impact on daily movements of the EURUSD exchange rate. Furthermore, they find asymmetries in the response of the exchange rate to news, but to different extents at different times. The authors model news as surprises, measured by the difference between the actual values of macroeconomic variables and the market's forecast, so that they use the median of survey data to measure market expectations. While Galati and Ho [2003] attempt to identifying sentiment on the EURUSD exchange rate, their study falls short of broader sentiment measures that might affect the exchange rate based on other interpretation of news than solely macroeconomic variables versus the market's forecast, such as geopolitical events, monetary policy outlook, such as potential rate hikes or cuts, quantitative easing, as well as other information. We can capture all of these topics with our news sentiment measure. Monetary policy also has a significant impact on exchange rates, as Conrad and Lamla [2010] show the impact of the European Central Bank's monetary policy communication on future price developments of the EURUSD exchange rate. On a similar note, Ehrmann and Fratzscher [2005] find that economic news in the US and in the Euro area are driving daily exchange rate developments of the EURUSD, and the exchange rate shows a greater reaction to news in periods of high volatility and heightened uncertainty.

In terms of the time period that the exchange rate is impacted by news announcements, Evans and Lyons [2008] exmaine intraday data on the DM/USD exchange rate and show that the arrival of macroeconomic news can account for more than 30% of daily price variance. Furthermore, Bauwens et al [2005] show that volatility in the EURUSD exchange rate increases in the pre-announcement periods, particularly before scheduled news events. They find that market activity also significantly impacts return volatility. Heiden et al [2013] examine the relation between investor sentiment and exchange rate movements (namely the USD/EUR exchange rate). They find that institutional sentiment significantly predicts returns over medium-term horizons in the USD/EUR market. Evans and Lyons [2005] find that currency markets are not responding to news instantaneously, which opens up the question for this study whether there are longer-term cycles of news sentiment impacting the USD/EUR exchange rate.

1.3 Data

In the following section, the data to be applied is explained and examined in greater detail. The data for the USD/EUR exchange rate was obtained from Thomson Reuters Datastream for the period 1975 - 2014.[1] The news sentiment data is extracted from Thomson Reuters ("NewsAnalytics") and captures positive, neutral and negative sentiment in news articles for the period 2003 - 2014.[2] The data are constructed in a two stage approach and with a natural language processing algorithm. First, positive, neutral and negative key-words are assigned with the so-called "bag of words" approach. After an initial automated analysis, a learning algorithm is applied to the content of the news articles, which is derived from articles analyzed for positive and negative sentiment by hundreds of financial market experts and economists. The resulting sentiment scores were used as input into the adaptive algorithm, leading to a coding classifier that is able to identify positive, neutral and negative sentiment within a context or topic.[3] The news sentiment data is available as high frequency tick data related to a wide variety of topic classifiers.[4] In order to obtain the news sentiment scores, the news sentiment items are filtered for topics relating to the EURO exchange rate only. In a second step, we aggregate the news sentiment tick data to weekly frequency. Note that data from Saturdays and Sundays were excluded because the news proved to be mainly

[1] Note that the time-series data for the EURUSD was re-constructed backwards by Thomson Reuters before the inception of the EURO.

[2] See Thomson Reuters News Analytics, http://thomsonreuters.com/products_services/financial/financial_products/quantitative_research_trading/news_analytics, last accessed 7 September 2010.

[3] See also Leinweber and Sisk [2011] and Uhl et al [2015] for more information on this dataset.

[4] The topics range from geopolitical, terror, war, individual company, credit rating,or monetary policy news, categorized into topic codes. See *Reuters Codes – A quick guide*, available at https://customers.reuters.com/training/trainingCRMdata/promo_content/ReutersCodes.pdf, last accessed 9 December 2010.

repetitive from the weekdays.[5]

As outlined above, we only consider two time series for this paper: the news sentiment data as well as the USD/EUR foreign exchange data. Figure 1 depicts both time series. We can see that the time series for news sentiment are extremely noisy, and at firsts sight do not have a clear relationship with the USD/EUR exchange rate. Hence, further analysis in greater detail is needed. When looking at the statistical properties of these time series, as shown in table 1, we note that the news sentiment time series is stationary, whereas the USD/EUR exchange rate is not stationary. Therefore, for the succeeding analysis, we take log differences for the USD/EUR exchange rate when used as dependent variable.

2.1 Filtering out the noise

Lam and Yam [1997] have suggested using filter techniques for identifying price momentum in financial markets. Uhl et al [2015] apply this concept for filtering news sentiment momentum with the CUSUM filter method. This paper draws on these concepts: we want to filter out the noise in the underlying news sentiment time series in order to get a clear indication whether news sentiment is positive or negative, ideally over a time horizon of several weeks or months, by filtering out the noise.

In order to extract relevant parts of the signal and remove high frequency noise, we filter the news sentiment time series. Given that we want to extract noise out of the news sentiment signal, we apply a low-pass filter as low frequencies pass through more easily than higher frequencies. As in Oppenheim and Schafer [1989], the filter method used is a simple low-pass filter implemented as a direct form II transposed structure as follows:

$$\begin{aligned} y(n) = b(1) * x(n) + b(2) * x(n-1) + \ldots + b(nb+1) * x(n-nb) \ldots \\ -a(2) * y(n-1) - \ldots - a(na+1) * y(n-na), \end{aligned} \tag{1}$$

[5] The database used for these operations is kdb+.

where $n-1$ is the filter order, na is the feedback filter order, and nb is the feedforward filter order. See Appendix A.1 for the time domain difference equations. According to standard theory and as in Harris [1978], we set $a = 1$. Furthermore, we set $b \neq 1$ by chosing several windows, as presented in Harris [1978]. The following windows are taken into account: the Hanning, Hamming, Bohman, Tukey, Cauchy, Riemann, Riesz, Poisson, and Hanning-Poisson. With these window techniques, we want to take account of the relevance decay in time of the data filtered as well as for potential non-linearity in the data. See Appendix A.2 for a detailed description of the windows analyzed in this study. Figure 2 shows a graphical representation of the windows used for the parameter b.

We want to particularly stress that the idea of filtering with these harmonic windows is neither a simple data mining exercise as to which window performs best nor an extensive survey of all harmonic windows in the literature. Rather, we have consulted the literature of frequency filtering and identified several of the most common windows with differing characteristics, which we want to test, as graphically shown in figure 2. We first apply the windows with the low-pass filter to the Euro-specific news sentiment data. Then, in a second step, we want to cross-check the filtered news sentiment data against filtered time series of the USD/EUR exchange rate itself, filtered with the windows as specified before. Therefore, we can compare price momentum and news sentiment momentum for the USD/EUR, which was computed based on the same low-pass filtering method with several windows as described above.

2.2 Sentiment and Momentum in the EURUSD exchange rate

As outlined above, we filter with a low-pass filter and apply the above specified harmonic windows. In a first step, we filter the Euro-specific news sentiment with the harmonic windows. Then, we run simple ordinary-least squares (OLS) regressions with the filtered news sentiment time series (with one day lag to account for data availability) on the log differences of the USD/EUR exchange rates. For all regressions, we derive heteroskedasticity consistent covariance matrices according to Newey West [1987]. The results are shown in table 2. We can see that all news sentiment coefficients are statistically significant. The sign of the news sentiment coefficients is negative for all windows, which is intuitive, as we have a Euro-specific news sentiment and we run the regression on the USD/EUR exchange rate.[6] So this means that if news sentiment is positive, the USD/EUR rate should go down. In order to test the robustness of the results, we have run all regressions with lags up to 10 days for news sentiment. Table 3 shows the consolidated results, which indicate that most of the windows used for most lags up to 10 days are statistically significant. This speaks for robust results, and does not indicate that filtering with these windows is arbitrary or coincidence. As anticipated, we also note that it is not of too much importance which window is applied in the filtering process. Rather, the mere process of filtering with a low pass-filter and applying non-linear windows does the job in filtering out the noise of the news sentiment data. This is particularly important for the next section, in which we want to construct trading strategies. The smoothing of the time series is of particular interest so that the position does not change too often (and creates excessive trading costs), when we create a trading strategy based on the data later.

In a second step, we filter for price momentum in the USD/EUR exchange rate with the windows as described above in order to being able to compare it to news sentiment. We want to test how the filtered news sentiment compares to filtered price data for the USD/EUR exchange rate. Then, as above, we run ordinary least-squares regressions with the filtered price momentum time series of the USD/EUR on the USD/EUR exchange rate time series. The results are shown in table 4. Also here, we can see that for all windows used, the coefficients for price momentum are statistically significant and positive. This means that momentum is positively correlated with subsequent changes in the exchange rate. So if we

[6] Note that if we used the EURUSD exchange rate, the coefficient sign would have been positive.

invest in momentum, we should buy when momentum is positive, and sell when momentum is negative.

Furthermore, given that we have two sets of independent variables, namely news sentiment and price momentum, we want to test how similar or different they are to each other. We therefore compute simple correlations between each of the filtered time series. Table 5 shows the results across the two variables and for all windows used. Across all windows, price momentum and news sentiment is not correlated to each other. Rather, the two variables are slightly negatively correlated (between 0 and -0.2). This suggests to us that the two indicators are significantly different to each other, so that we can assume that we have found a new factor with news sentiment over price momentum. In the next section, we want to apply our findings in a real trading strategy.

2.3 Trading strategies based on sentiment and momentum

As outlined above, the econometric results are quite promising that the filtered time series for news sentiment and price momentum can also be applied in a trading strategy. In order to do this, we take the time series as signals for being invested in the USD/EUR exchange rate. First, we build a long-short trading strategy with price momentum, the more traditional way of building a trading strategy. In a second step, we construct a trading strategy with news sentiment in order to compare the results from the two variables.

For the momentum strategy, if the signal is positive, we go long the USD/EUR exchange rate, in line with the findings from the regressions, as the coefficient for momentum is positive on the USD/EUR exchange rate. The implementation lag is one day in order to account for data availability. We have not included transaction costs because the USD/EUR exchange rate is the most traded currency pair and implementation costs are only a few basis points, if at all. We construct the trading strategy since end December 2004 until end of December 2014 in order to being able to compare it later with the trading strategy based on news sentiment, as we only have filtered news sentiment data as of 2004. The trading strategy is constructed as an out-of-sample backtest, i.e. it is simulated as if the trading strategy were implemented live. Table 6 shows the results of the trading strategies for the filtered time series with all eight windows. Over the whole backtesting period of ten years, the mean return per year for each of the strategies is positive and around 4% with an annual volatility of 10%. The maximum drawdown for each of the strategies is higher than -20%. The information ratio sets the returns in relation to the volatility, and these are around 0.4. This is quite a good value, especially when comparing to other momentum studies of a similar kind. For instance, Asness et al [2013] have shown that momentum offers return premia across financial markets and asset classes, including currencies. In their study, Asness et al [2013] achieve an information ratio for their currency momentum strategy of 0.29. All of our strategies achieve a higher information ratio. Given that we compute the momentum differently, we can assume that our method of calculating momentum is superior than the one applied in Asness et al [2013]. Furthermore, the strategies only switch very little, namely between 4 and 9 times per year. This strongly suggests to us that we have indeed filtered out the noise in order to get a consistent trend estimate over a longer period of time.

Second, we build a long-short strategy based on news sentiment. In accordance with our findings from the regressions and the negative coefficient of news sentiment when regressed on the USD/EUR exchange rate (because the sentiment is Euro-specific), we go long the USD/EUR exchange rate when the signal is negative, and we go short the USD/EUR exchange rate when the signal is positive. As in the previous trading strategy, we construct this strategy in an out-of-sample environment, do not charge transaction costs and implement with one day lag. The results are shown in table 7. The mean returns per year for each of the strategies based on news sentiment are on average between 5% and 9%. That is basically double the returns of the strategies based on price momentum. The annual volatility is similar at 9.9%, but the maximum drawdowns are also lower than for price momentum on average. Given similar volatility and almost double annual returns, the information ratios are also roughly twice as high as for price momentum, ranging from 0.5 to 0.9. The switches per year are also higher than for price momentum, ranging from 10 to 18. On average, the strategy based on news sentiment switches once per month, which is still quite low and easy to implement without generating excessive trading costs.

We have shown that filtering with low-pass filters and several harmonic windows for both price momentum and news sentiment generates significant alpha and high information ratios for absolute return strategies for the USD/EUR exchange rate. Filtering for noise is beneficial for identifying trends in the exchange rate, enabling the investor not to trade too often, at most once a month on average for news sentiment, and half of that for price momentum strategies.

3.1 Conclusion

We close a gap in the foreign exchange literature by introducing news sentiment as a variable that can explain and predict subsequent changes in the USD/EUR exchange rate. By applying the concept of frequency filtering from the domain of electrical engineering, we show an innovative way of filtering for noise in both news sentiment, but also in price momentum. We find that news sentiment is not correlated to price momentum, and that trading strategies based on news sentiment achieve around twice as high information ratios (up to 0.9) than with trading strategies based on price momentum.

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Appendix A.1

The time domain difference equations are as follows:

$$
\begin{aligned}
y(m) &= b(1)\,x(m) + z_1(m-1) \\
z_1(m) &= b(2)\,x(m) + z_2(m-1) - a(2)\,y(m) \\
\vdots &= \vdots\ \vdots \\
z_{n-2}(m) &= b(n-1)\,x(m) + z_{n-1}(m-1) - a(n-1)\,y(m) \\
z_{n-1}(m) &= b(n)\,x(m) - a(n)\,y(m).
\end{aligned} \tag{2}
$$

The input-output description of this filtering operation in the z-transform domain is a rational transfer function:

$$
Y(z) = \frac{b(1) + b(2)\,z^{-1} + \ldots + b(nb+1)\,z^{-nb}}{1 + a(2)\,z^{-1} + \ldots + a(na+1)\,z^{-na}} X(z). \tag{3}
$$

Appendix A.2

The Hamming window is defined as follows:

$$
b(n) = 0.54 - 0.46 * \cos\left(\frac{2\pi n}{N-1}\right).
$$

The Tukey window is defined as follows:

$$
b(n) \begin{cases} 1.0, & 0 \le |n| \le \alpha\frac{N}{2} \\ 0.5\left[1.0 + \cos\left[\pi\frac{n-\alpha\frac{N}{2}}{2(1-\alpha)\frac{N}{2}}\right]\right], & \alpha\frac{N}{2} \le |n| \le \frac{N}{2} \end{cases}.
$$

The Cauchy window is defined as follows:

$$
b(n) = \frac{1}{\left(1 + \left(\frac{\alpha * n * N}{2}\right)\right)}.
$$

The Riesz window is defined as follows:

$$b\left(n\right) = 1 - \left(\frac{n}{N/2}\right)^2.$$

The Poisson window is defined as follows:

$$b\left(n\right) = \exp\left(\frac{-\alpha * n * N}{2}\right).$$

The Hanning-Poisson window is defined as follows:

$$b\left(n\right) = 0.5 * \left(\left(1 + \cos\left(\frac{\pi * n}{N/2}\right)\right) * \exp\left(\frac{-\alpha * n}{N/2}\right)\right).$$

The Hanning window is defined as follows:

$$b\left(n\right) = 0.5 * \left(1 - \cos\left(\frac{2\pi n}{(N-1)}\right)\right).$$

The Bohman window is defined as follows:

$$b\left(n\right) = \left[1 - \frac{|n|}{N/2}\right]\cos\left[\pi\frac{|n|}{N/2}\right] + \frac{1}{\pi}\sin\left[\pi\frac{|n|}{N/2}\right].$$

For all of the above (except for the Tukey window), we have: $0 \leq |n| \leq \frac{N}{2}$. The reader is invited to consult Harris [1978] for further information on the several windows.

Figure 1: EURUSD Exchange Rate and News Sentiment (raw weekly aggregated data)

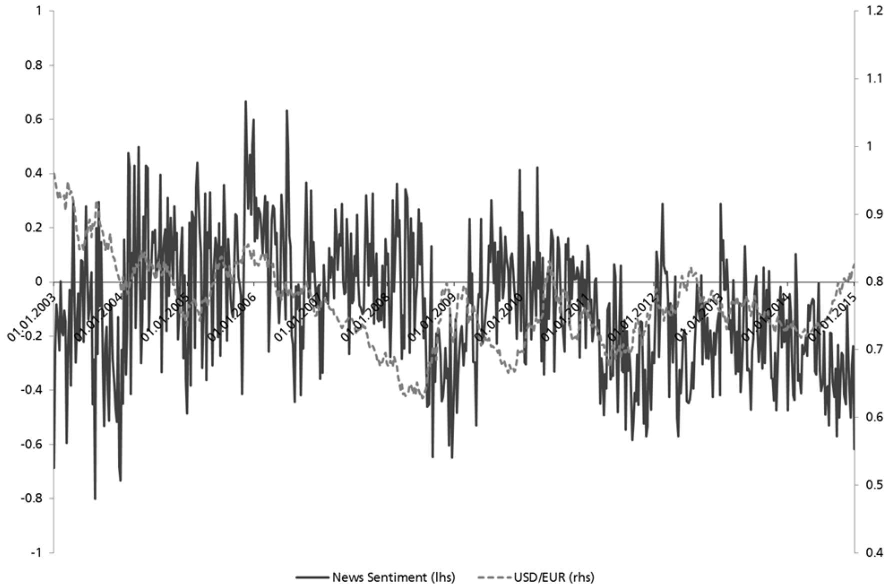

Table 1: Descriptive statistics and unit root tests of EURUSD exchange rate and news sentiment

	USD/EUR FX Rate	EURUSD News Sentiment
Mean	0.825837	-0.090459
Median	0.79	-0.089741
Maximum	1.438	0.666667
Minimum	0.543	-0.800000
Standard Deviation	0.158325	0.243369
Augmented Dickey- Fuller Unit Root test statistic - Null Hypothesis: Has a unit root (t-Statistic)	0.2552 (-2.074687)	**0.0000** (-4.879459)

Figure 2: Harmonic windows applied to EURUSD news sentiment and price momentum

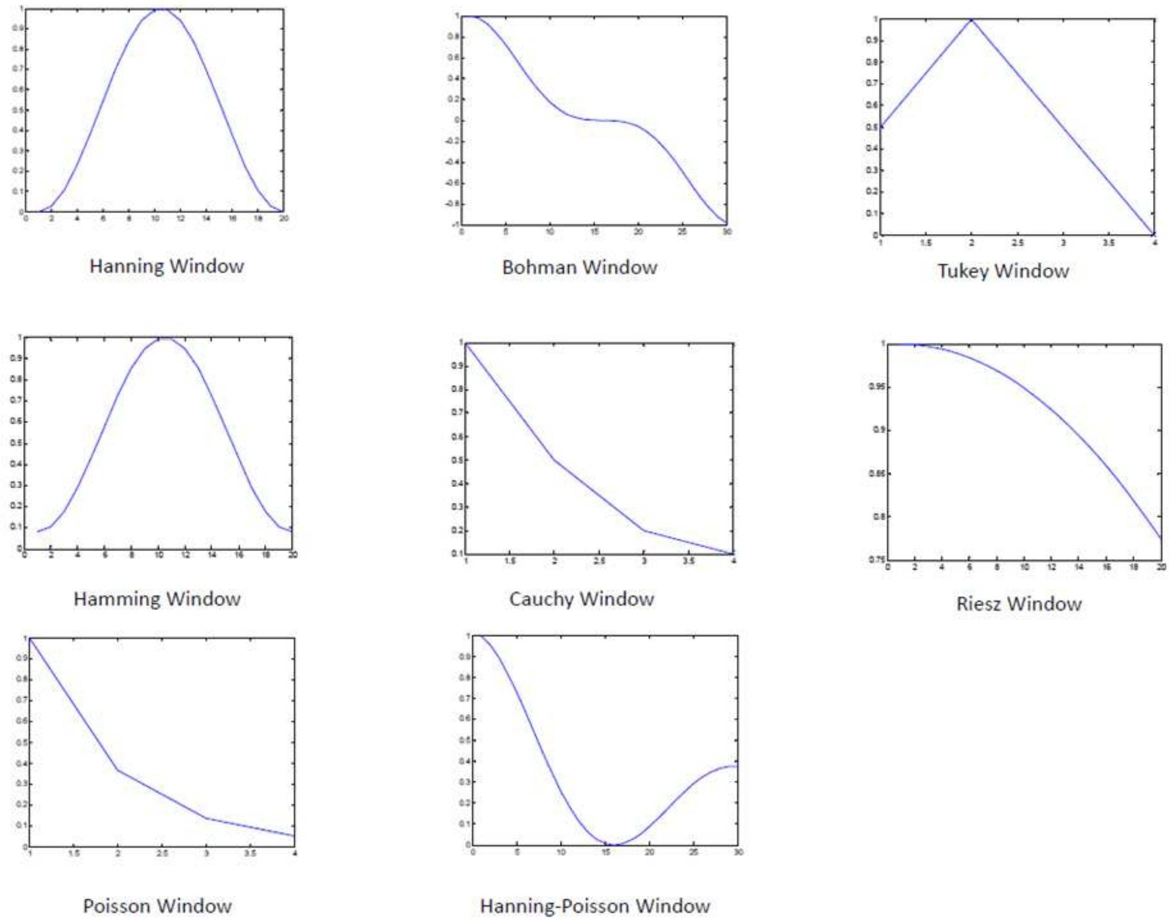

Table 2: Ordinary least square regressions on EURUSD exchange rate with EURUSD news sentiment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2003 - 2014	2003 - 2014	2003 - 2014	2003 - 2014	2003 - 2014	2003 - 2014	2003 - 2014	2003 - 2014
	Hamming Window	Tukey Window	Cauchy Window	Riesz Window	Poisson Window	Hanning-Poisson Window	Hanning Window	Bohman Window
Dependent variable: USD/EUR exchange rate (log returns)								
News Sentiment (-1)*	**-0.000309**	**-0.000341**	**-0.00037**	**-0.000358**	**-0.00037**	**-0.000372**	**-0.000282**	**-0.000453**
	(-1.935335)	*(-2.049412)*	*(-2.211695)*	*(-2.224097)*	*(-2.229273)*	*(-2.249794)*	*(-1.859776)*	*(-2.985793)*
Constant	0.0000749	-0.0000872	-0.0000699	-0.0000736	-0.0000711	-0.0000682	-0.0000703	-0.0000685
	(-0.688994)	*(-0.811845)*	*(-0.648690)*	*(-0.682690)*	*(-0.660829)*	*(-0.631757)*	*(-0.642406)*	*(-0.626920)*
Trading Days	3131	3131	3131	3131	3131	3131	3131	3131
Adjusted R-squared	0.001206	0.001753	0.001876	0.001964	0.001857	0.00184	0.001007	0.002402

Robust t-statistics according to Newey-West in parentheses, coefficients in bold are statistically significant
* Low-pass filter with chosen window as specified in each column.

Table 3: OLS-regressions of news sentiment with various lag lengths on the USD/EUR exchange rate

OLS Regression: DLOG(USDEUR) News Sentiment(-*lag*)* Constant

Statistically Significant Coefficients	Bohman Window	Cauchy Window	Hamming Window	Hanning-Poisson Window	Hanning Window	Poisson Window	Riesz Window	Tukey Window
Lags								
-1	√	√	√	√	√	√	√	√
-2	√	√	√	X	X	X	√	√
-3	√	√	√	√	X	√	√	√
-4	√	√	√	√	X	√	√	√
-5	√	X	√	X	√	X	√	√
-6	√	√	√	√	√	√	√	√
-7	√	√	√	√	√	√	√	√
-8	√	X	√	√	√	√	X	√
-9	√	X	√	√	√	√	X	√
-10	√	√	X	√	√	√	X	X

* News Sentiment as independent variable with lag and window as specified.

Table 4: Ordinary least square regressions on EURUSD exchange rate with EURUSD price momentum

	(1) 1975 - 2014 Hamming Window	(2) 1975 - 2014 Tukey Window	(3) 1975 - 2014 Cauchy Window	(4) 1975 - 2014 Riesz Window	(5) 1975 - 2014 Poisson Window	(6) 1975 - 2014 Hanning-Poisson Window	(7) 1975 - 2014 Hanning Window	(8) 1975 - 2014 Bohman Window
Dependent variable: USD/EUR exchange rate (log returns)								
Momentum (-1)*	**0.000132**	**0.000164**	**0.000169**	**0.000126**	**0.000171**	**0.000135**	**0.000117**	**0.000115**
	(3.520365)	*(3.756607)*	*(3.915668)*	*(3.477752)*	*(3.928990)*	*(3.652803)*	*(3.054056)*	*(2.450709)*
Constant	0.0000336	0.0000312	0.000031	0.0000341	0.0000308	0.0000349	0.000034	0.0000374
	(0.552594)	*(0.526772)*	*(0.525027)*	*(0.561900)*	*(0.523337)*	*(0.579685)*	*(0.557463)*	*(0.619427)*
Trading Days	10437	10437	10437	10437	10437	10437	10437	10437
Adjusted R-squared	0.001275	0.001381	0.00147	0.001244	0.001469	0.001372	0.000976	0.000608

Robust t-statistics according to Newey-West in parentheses, coefficients in bold are statistically significant

* Low-pass filter with chosen window as specified in each column.

Table 5: Correlation Analysis between filtered time-series of EURUSD exchange rate (price momentum) and EURUSD news sentiment

Correlation
(statistically significant values in bold, t-statistic in parentheses)

2003 - 2014	***News Sentiment:***	Bohman Window	Cauchy Window	Hamming Window	Hanning-Poisson Window	Hanning Window	Poisson Window	Riesz Window	Tukey Window
Price Momentum:									
Bohman Window		**-0.16** (-8.835453)							
Cauchy Window		**-0.15** (-8.7517)	**-0.19** (-10.68051)						
Hamming Window		**-0.05** (-2.552508)	**-0.11** (-6.096313)	**-0.11** (-6.309037)					
Hanning-Poisson Window		**-0.10** (-5.572459)	**-0.15** (-8.412854)	**-0.15** (-8.655551)	**-0.14** (-7.824014)				
Hanning Window		**-0.04** (-2.431619)	**-0.10** (-5.881543)	**-0.11** (-6.156284)	**-0.09** (-5.055938)	**-0.10** (-5.700296)			
Poisson Window		**-0.15** (-8.738547)	**-0.19** (-10.68096)	**-0.17** (-9.910925)	**-0.18** (-10.19453)	**-0.16** (-9.228964)	**-0.18** (-10.47209)		
Riesz Window		**-0.07** (-3.984177)	**-0.13** (-7.59038)	**-0.13** (-7.451874)	**-0.12** (-6.803421)	**-0.12** (-6.928228)	**-0.13** (-7.245989)	**-0.16** (-9.081934)	
Tukey Window		**-0.15** (-8.537857)	**-0.18** (-10.39598)	**-0.17** (-9.589858)	**-0.17** (-9.936513)	**-0.16** (-8.906785)	**-0.18** (-10.20824)	**-0.20** (-11.47924)	**-0.20** (-11.68731)

Table 6: Long-Short trading strategy based on EURUSD price momentum

EURUSD Price Momentum

	Mean return p.a.	*Volatility p.a.*	*MaxDD*	*Information Ratio*	*Switches p.a.*
Hanning	4.2%	10.0%	-20.7%	0.42	4.4
Bohman	3.3%	10.0%	-20.1%	0.33	8.0
Tukey	3.5%	10.0%	-21.5%	0.35	8.8
Hamming	4.7%	10.0%	-20.7%	0.47	4.4
Cauchy	3.5%	10.0%	-23.3%	0.35	9.0
Riesz	4.8%	10.0%	-21.4%	0.48	3.6
Poisson	3.6%	10.0%	-22.3%	0.36	9.6
Hanning-Poisson	4.3%	10.0%	-22.9%	0.43	3.5

Data from 12/2004 - 12/2014, Benchmark 0%

Table 7: Long-Short trading strategy based on EURUSD news sentiment

EURUSD News Sentiment

	Mean return p.a.	*Volatility p.a.*	*MaxDD*	*Information Ratio*	*Switches p.a.*
Hanning	7.3%	9.9%	-16.8%	0.74	18.0
Bohman	8.9%	9.9%	-20.8%	0.6	12.5
Tukey	9.2%	9.9%	-16.6%	0.93	10.4
Hamming	6.6%	9.9%	-16.8%	0.67	15.5
Cauchy	5.3%	9.9%	-25.0%	0.54	12.4
Riesz	7.1%	9.9%	-18.0%	0.72	10.6
Poisson	6.4%	9.9%	-17.9%	0.65	13.6
Hanning-Poisson	6.1%	9.9%	-15.5%	0.62	14.7

Data from 12/2004 - 12/2014, Benchmark 0%